

A Meta-Analysis of Factors Influencing the Development of Trust in Automation: Implications for Human-Robot Interaction

**by Kristin E. Schaefer, Deborah R. Billings, James L. Szalma,
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ARL-TR-6984

July 2014

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ARL-TR-6984

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REPORT DOCUMENTATION PAGE			Form Approved OMB No. 0704-0188		
<p>Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing the burden, to Department of Defense, Washington Headquarters Services, Directorate for Information Operations and Reports (0704-0188), 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302. Respondents should be aware that notwithstanding any other provision of law, no person shall be subject to any penalty for failing to comply with a collection of information if it does not display a currently valid OMB control number.</p> <p>PLEASE DO NOT RETURN YOUR FORM TO THE ABOVE ADDRESS.</p>					
1. REPORT DATE (DD-MM-YYYY)	2. REPORT TYPE		3. DATES COVERED (From - To)		
July 2014	Final		September 2012–February 2014		
4. TITLE AND SUBTITLE			5a. CONTRACT NUMBER		
A Meta-Analysis of Factors Influencing the Development of Trust in Automation: Implications for Human-Robot Interaction			5b. GRANT NUMBER		
			5c. PROGRAM ELEMENT NUMBER		
6. AUTHOR(S)			5d. PROJECT NUMBER		
Kristin E. Schaefer, Deborah R. Billings, James L. Szalma, Jeffrey K. Adams, Tracy L. Sanders, Jessie Y. C. Chen, and Peter A. Hancock			5e. TASK NUMBER		
			5f. WORK UNIT NUMBER		
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)			8. PERFORMING ORGANIZATION REPORT NUMBER		
U.S. Army Research Laboratory ATTN: RDRL-HRS-E Aberdeen Proving Ground, MD 21005-5425			ARL-TR-6984		
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)			10. SPONSOR/MONITOR'S ACRONYM(S)		
			11. SPONSOR/MONITOR'S REPORT NUMBER(S)		
12. DISTRIBUTION/AVAILABILITY STATEMENT					
Approved for public release, distribution is unlimited.					
13. SUPPLEMENTARY NOTES					
14. ABSTRACT					
Trust has become increasingly important because of the increasing need for synergistic human-machine teaming. Here, we expand on our previous meta-analytic work in the field of human-robot interaction (HRI) to include all of human-automation interaction. We used meta-analytic procedures to assess trust. A total of 343 articles were reviewed, of which 30 studies, providing 164 effect sizes, and 16 studies, providing 63 correlational effect sizes, met the selection criteria for analysis. The overall experimental effect on trust was $\bar{g} = +0.48$, and the correlational effect was $\bar{r} = +0.34$, each of which represented a medium to strong effect. Moderator effects were examined for the human-related ($\bar{g} = +0.49$; $\bar{r} = +0.16$) and automation-related ($\bar{g} = +0.53$; $\bar{r} = +0.41$) factors. However, moderator effects specific to the environmental factors were not calculated because of a lack of presently qualified studies. Submoderating factors were examined and reported for human-related (i.e., age, cognitive factors, emotive factors) and automation-related (i.e., features and capabilities) effects. Analyses were also conducted for type of automated aid: cognitive, control, and perceptual automation aids. Automated cognitive aids provide recommendations to users about the current and potential future states of systems. Automated control aids replace varying levels of human (operator, user) action. Perceptual aids are used to assist the operator or user by providing warnings or to assist with pattern recognition. All three types of aids—cognitive ($\bar{g} = +0.41$; $\bar{r} = +0.39$), control ($\bar{g} = +0.51$; $\bar{r} = +0.12$), and perceptual ($\bar{g} = +0.62$; $\bar{r} = +0.37$)—had a moderate effect on trust development. These findings provide a quantitative picture of human-, automation-, and environment-related factors influencing trust in automation. Findings from this work were used to develop design and training guidelines that are also applicable to HRI. Future research needs were identified based on the results of the foregoing analyses.					
15. SUBJECT TERMS					
automation, human-machine interaction, meta-analysis, robot, trust					
16. SECURITY CLASSIFICATION OF:		17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON	
a. REPORT	b. ABSTRACT			c. THIS PAGE	Kristin E. Schaefer
Unclassified	Unclassified	Unclassified	UU	70	19b. TELEPHONE NUMBER (Include area code) 410-278-5972

Contents

List of Figures	v
List of Tables	v
Acknowledgments	vi
1. Introduction	1
1.1 Foundation.....	2
1.2 Definitions.....	3
1.3 Report Organization	4
2. Task-Specific Trust in Automation	5
2.1 Trust in Cognitive Aids	5
2.2 Trust in Control Aids.....	7
2.3 Trust in Perceptual Aids	8
3. Development of a Trust-in-Automation Model	8
3.1 Theoretical Model of Human-Automation Trust	9
3.2 Factors Associated With the Human.....	10
3.2.1 Operator Traits and States	10
3.2.2 Cognitive Factors	11
3.2.3 Emotive Factors.....	13
3.3 Factors Associated With the Automation.....	14
3.3.1 Feature-Based Characteristics	14
3.3.2 Automation Capability	16
3.4 Factors Associated With the Environment.....	19
4. Analytical Method	19
4.1 Sample of Studies.....	19
4.2 Criteria for Study Inclusion.....	19
4.3 Coding of Studies	20
4.4 Effect Size	21
4.5 Variance Estimates	21

5. Results	21
5.1 Preference for Human or Automation Assistance.....	21
5.2 Task-related Automation.....	22
5.3 Human-Related Factors	23
5.4 Automation-Related Factors.....	24
6. Discussion	25
6.1 Training Suggestions	26
6.2 Design Recommendations.....	26
7. Conclusions	28
8. References	29
Appendix A. Definitions	43
Appendix B. Comprehensive Automation Trust Definition Set	45
Appendix C. References of Experimental and Correlational Articles	51
Appendix D. Organization Results	57
Distribution List	61

List of Figures

Figure 1. Human-Robot trust (Hancock et al., 2011).	2
Figure 2. Antecedents of trust from definitions of trust in automation.	9
Figure 3. Theoretical model of human-automation trust.	10
Figure 4. Revised human-robot descriptive trust model.	25
Figure 5. Levels of automation (Parasuraman et al., 2000).	27

List of Tables

Table 1. Task-dependent antecedents of trust in cognitive automation.	6
Table 2. Task-dependent antecedents of trust in control automation.	7
Table 3. Meta-analytic results for perception of trust in a human or automation for a task.	22
Table 4. Meta-analytic results for trust in task-based automation.	23
Table 5. Meta-analytic results for human-related factors on trust in automation.	24
Table 6. Meta-analytic results for automation-related factors on trust in automation.	24

Acknowledgments

Research was sponsored by the U.S. Army Research Laboratory (ARL) and was accomplished under Cooperative Agreement Number W911NF-10-2-0016. The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of ARL or the U.S. Government. The U.S. Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation herein. The authors would like to thank our reviewers Dr. Raja Parasuraman, Dr. Ewart de Visser, and Andrea Krausman for their detailed feedback and recommendations.

1. Introduction

The purpose of this report is to review the current evidence relating to trust in human-automation interaction and to compare these findings with our prior research on the more specific area of trust in human-robot interaction (HRI) (Hancock et al., 2011). Since automation has been shown to be a key dimension of a robot (including unmanned systems), identifying the factors that can impact trust between humans and automation may significantly increase our understanding of trust and its applications to HRI.

Previous meta-analytic findings on human-robot trust helped to formulate and formalize a triadic model of trust, which categorized the factors influencing trust development as human-related, robot-related, or environment-related characteristics (figure 1) (Hancock et al., 2011). Hancock and his colleagues (2011) established the great importance of robot performance consistency (e.g., reliability) and allied attributes in the development of trust in HRI. Environmental characteristics (e.g., team collaboration, task type) were found to influence trust in HRI but only to a lesser degree than the reliability factor. Further, this work revealed that human-related factors did not appear to play a large role in the development of trust; however, limited empirical research was available regarding human-related dimensions and the influences on trust in robots at the present time. The resulting model of HRI trust must thus be interpreted with caution, as the descriptive model may change as the dearth of current experimentation was addressed. Additionally, the research used to construct the trust model was limited only to empirical studies documenting human interaction with embodied robots, which is a specific subfield of automation. Thus, our prior meta-analysis did not include an assessment of all other types of automation (e.g., decision support systems). Consequently, an examination of the trust in the larger body of automation literature may increase our understanding of human-robot trust. The following represents this effort using a quantified meta-analytic technique.

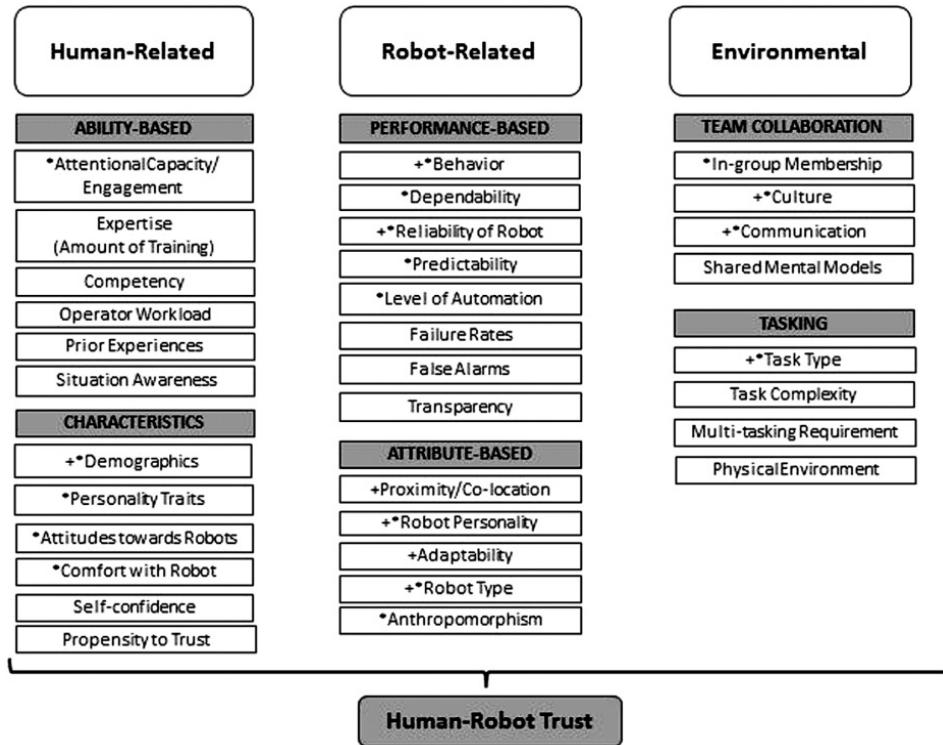


Figure 1. Human-Robot trust (Hancock et al., 2011).

1.1 Foundation

Technical developments have made it possible to automate tasks that have traditionally been carried out by humans. Automated systems can be used in environments that are high risk for humans (e.g., hazardous, life-threatening environments), in tasks that humans do not want to perform (e.g., boring and repetitious tasks), and in tasks where a machine is more accurate or reliable than a human (e.g., mathematical computations, robotics manufacturing, and autopilot activity). Parasuraman and colleagues (2000) have provided a review of system functions that can and should be automated based on their cost of action consequences on human performance. As such, automation is now available in multiple domains, from the home (e.g., refrigerator) to the local environment (e.g., automated teller machine) to the battlefield (e.g., unmanned vehicles). For example, within robotics, unmanned aerial systems are designed to be used in situations where machines provided better sustained performance than a human, when there are differing political and human costs in high-risk environments, and when there is an increased likelihood for mission success (Office of the Secretary of Defense, 2005). Further, in the final Task Force Report on the role of autonomy in Department of Defense systems, the Defense Science Board (DBS, 2012) suggested that unmanned systems are making a significant impact on warfare worldwide. This report stated that the value of unmanned systems is not the replacement of a human but human-system collaboration (i.e., the capability to extend and complement human capability without degradation because of fatigue or lack of attention); however, the major challenge is the lack of trust that the system will perform as intended.

In addition, automation literature has explored the impacts of trust on performance outcomes and trust calibration strategies in greater depth than traditional human-robot trust literature. For example, trust in automation is directly tied to the outcome measurements of human-automation interaction, specifically automation use (see Beck et al., 2007; Moray et al., 2000; Muir and Moray, 1996; Parasuraman et al., 1993). These include human reliance on automation and human compliance with automation (see also Barnett, 2007; Chen and Terrence, 2009; Dzindolet et al., 2003; Lee and Moray, 1992; Lee and Moray, 1994; Lee and See, 2004). In addition, trust development is related to performance outcomes that lead to safety decisions (see Maltz and Meyer, 2001; Scallen and Hancock, 2001; Schobel, 2009; Schobel and Manzey, 2011; Seppelt and Lee, 2007; Yamada and Kuchar, 2006). Appropriate trust calibration is critical for appropriate reliance on automation for all types of automated aids. According to Lee and Moray (1994), trust calibration pertains to the trust level of the human user and its correspondence to the capabilities of the automated aid. As such, too much trust may lead to overreliance, complacency, and mistrust, while too little trust can lead to disuse. Properly calibrated trust creates a situation where the human user is engaged with the automation and participates at the appropriate level in the process (Muir, 1994). Calibration of trust is also an important issue for computer users in the e-commerce domain. Bonsall and Joint (1991) suggested that users have difficulties placing the “right level” of trust in computer advice systems. Computer users also have difficulties heeding advice from a computer aid during the decision-making process (Hoffman et al., 1999; Ratnasingham, 1998).

1.2 Definitions

For the purpose of this work, it is important to understand the relationship between the terms *autonomy*, *automation*, and *robot*. Literature and human perception have often blurred the definitional lines between these terms. For example, automation and autonomy, as well as automation and robot, are often used interchangeably. Here, autonomy is defined as “a capability (or set of capabilities) that enables a particular action of a system to be automatic or, within programmed boundaries, ‘self-governing’” (DSB, 2012). Automation, in the broadest sense of the word, is a “machine execution of functions” (Parasuraman et al., 2000, p. 286). With such a broad definition of automation, it is no wonder there is confusion or overlap among the definitions of autonomy, automation, and robot. In addition, a large portion of automation-based definitions and theoretical contributions build on the work by Victor Riley (1989) that discussed automation states in terms of combinations of values along the dimensions of machine intelligence (i.e., degree of data processing) and autonomy (i.e., degree of authority to act on the “World”). For example, Parasuraman and Riley (1997) incorporated the human-machine comparison in which automation was defined as “the execution by a machine agent (usually a computer) of a function that was previously carried out by a human” (p. 231). In a more detailed view of the functions of the technology, Lee and See (2004) define automation as the “technology that actively selects data, transforms information, makes decisions, or controls processes” (p. 50).

A robot is often defined and discussed in terms of its functional and autonomous capabilities. This is illustrated by Mahoney's (1997) definition of a robot as "programmable automation to augment human manipulation" (p. 3). More recently, Yagoda (2011) defined a robot as the interaction of intelligence and autonomy, thus building on Riley's (1989) automation research and further linking the two definitions. However, additional work has also shown the importance of physical form or embodiment to the classification of a machine as a robot. For example, Kurfess (2005) suggested that a robot is the manifestation of human characteristics, such as complex actions and anthropomorphic features. Schaefer (2013) also provided a more complete review of the variations between robot definitions as well as additional experimentation on a human's perception of the classification of a machine as a robot.

In addition, Scholtz (2003) has suggested that the type of interaction, the number of systems a user may interact with, the environment, and the physical nature of the robot (e.g., complex, dynamic control systems, exhibition of autonomy and cognition) help differentiate HRI from more general human-computer or human-machine interaction. Steinfield et al. (2006) suggested that HRI can and should be discussed in terms of five types of tasks: navigation, perception (i.e., perceive and understand the remote environment for application), management (i.e., coordination of the actions of humans and robots), manipulation (i.e., interaction with the environment), and social tasks (i.e., perform tasks that require "social interaction"). Therefore, by taking into account the task-based nature of HRI, it may be more accurate to classify a robot as having varying or multiple autonomous capabilities within a single embodiment or system.

1.3 Report Organization

Section 2 identifies three types of task-specific automation (i.e., cognitive, control, and perceptual aids) and the importance to trust development within each type of automation aid. Section 3 outlines a descriptive model of human-automation trust and provides literary support for the model structure in terms of the human-related, automation-related, and environmental-related trust factors. Section 4 outlines the analytical methodology for the meta-analytic analysis provided in section 5. Section 6 reconnects the human-automation trust results with the potential links within HRI. Training suggestions, as well as design recommendations, are provided. This report is summated with a conclusion (section 7) addressing the importance of this work to the military domain.

2. Task-Specific Trust in Automation

Automation literature provides a number of insights into types of functions that may be automated across a variety of tasks. More importantly, task- and function-specific aspects of automation play an important role in the development of trust in these systems. Task-related automation is hereby broken down into three major areas of automation aids: cognitive, control, and perceptual aids. This accords with the framework discussed in Parasuraman et al. (2000) that identified types of automation as acquisition, analysis, decision, and action aids while taking into account that the task-related nature of automation elements is related to HRI.

2.1 Trust in Cognitive Aids

Automated cognitive aids provide recommendations to users about the current and potential future states of systems. These automated decision aids or expert systems can make accurate identifications or detections during a screening or inspection, monitoring, or route planning tasks. This type of aid has been used in many areas, including e-commerce, medication management domains, and many others (table 1).

In addition to these factors, Corritore et al. (2003) suggest that computer interface design criteria (e.g., ease of use, good visual design elements, information content, and reputation) can provide cues to the degree to which an aid will be perceived as trustworthy. One concern about cognitive aids is that operators may trust and rely excessively on the automated aid. This can lead to reduced monitoring and, in turn, increase the number of errors (e.g., decision-making task for pilots, Sarter and Schroeder, 2001). Similar findings were also shown by Bagheri and Jamieson (2004) during a monitoring task: increased trust in the automation led to lower operator error detection.

Table 1. Task-dependent antecedents of trust in cognitive automation.

Task	Antecedent of Trust	Finding
Target Detection (Chen and Terrence, 2009; Wang et al., 2009)	Reliability of automation	A more reliable aid led to more trust; however, this effect can be moderated by individual differences factors, such as operator attentional control.
Inspection Task (Madhavan and Wiegmann, 2007)	Expertise of Automation	Users trust expert automation more than novice automation.
	Human vs. automation	Users have more trust in a novice automated aid than a novice human, but more trust in an expert human than an expert automated aid.
	Task difficulty	Users trust an automated aid more when it is difficult to identify errors in the task.
Route Planning (Chen and Barnes, 2012; Cummings et al., 2010; De Vries and Midden, 2008)	Error rate of automation	When automation error rate is high, operators trust themselves more than the automation; conversely, when error rate is low, they trust automation more. However, these effects can be moderated by individual differences factors, such as operator attentional control.
	Risk	Participants who chose less risky paths trusted the automation more.
	Reputation	Operators had slightly higher trust when the automation had a positive reputation.
e-commerce (Aberg and Shahmehri, 2000)	Human vs. automation	Users preferred human assistance to automation.
Other Decision Aids (Ezer et al., 2008; Ho et al., 2005)	Reliability of automation	A more reliable aid led to more trust in the aid.
	Age of user	Older adults trusted automation more than younger adults; however, younger adults are more flexible than older adults in changing their reliance behavior based on the cost of verification (of the automation).

2.2 Trust in Control Aids

Automated control aids (e.g., autopilots, adaptive cruise control, and navigation aids) replace varying levels of human (operator or user) action. Operators tend to prefer automated control aids to traditional systems or procedures (Ardern-Jones et al., 2009). Trust is generally high for control aids. Initial trust tends to be higher for the automated aid (e.g., function allocation tasks, Ma and Kaber, 2007) and builds over time (Rajaonah, 2006). For a summary of factors impacting trust development of functional allocation tasks and vehicle control, see table 2.

Table 2. Task-dependent antecedents of trust in control automation.

Task	Antecedent of Trust	Finding
Function Allocation (Moray et al., 2000; Stedmon et al., 2007)	Reliability	Higher reliability led to higher trust.
	Communication mode	Operators had higher trust for automation that used human speech rather than synthetic speech.
	Communication accuracy	Operators had higher trust for accurate information than inaccurate information.
Vehicle Control: ACC, UAV (Donmez et al., 2006; Hughes et al., 2009; Spain and Bliss, 2008)	Age of user	Older drivers trusted adaptive cruise control (ACC) more than middle age drivers.
	Automation accuracy	Drivers trusted more accurate systems.
	Alarms	Drivers trusted visual alarms more than auditory alarms for vehicle control.
	Perceived usefulness of automation	As the level of usefulness of automation increased, so did trust.
	Human vs. automation	Users trusted pilot more than autopilot.
	Communication	Higher reliability of information led to higher trust.
	Workload	Trust was higher when workload was low.

Trust also has a direct impact on outcome measures. For example, Manzey and his colleagues (2009) found that most surgeons trust in the proper functioning of the navigational control tasks in a surgery system and would choose to be operated on by the system. More operator trust during function allocation tasks leads to more use, better performance, and less operator time manually adjusting the automation (Muir and Moray, 1996). In addition, higher reliability of adaptive cruise control (ACC) systems leads to more driver trust and increased compliance with the automation (Spain and Bliss, 2008).

2.3 Trust in Perceptual Aids

Perceptual aids are used to assist the operator or user by providing warnings (e.g., fault detection, automobile warning systems, and function allocation for signaling or communication) or to assist with pattern recognition (e.g., speech or target detection). For example, automobile warning systems are used for distraction mitigation, collision avoidance, and providing alarms (e.g., speed alerts). Gupta and colleagues (2002) assessed the effects of alarm type and alarm sensitivity (i.e., number of alarms) on drivers' trust of perception aids. They found no significant difference in type of alarm; however, drivers did show a higher trust for alarms with a low sensitivity rate. Similarly to the other two types of automation aids, users or operators of perception aids have more trust in people than in the automation. For example, Bisantz and Seong (2001) found that drivers using automobile warning systems had higher negative feelings of trust toward the automation when they were told that the failures were attributed to the hardware or software instead of people.

Trust in the warnings or alarms also has a direct effect on the outcome variables. One potential area for concern is the operator's overreliance on and over compliance with a warning system. Bitan and Meyer (2007) found that the impacts of the sensitivity rate and the false alarm rate on trust also have a direct impact on the user's reliance and compliance (respectively) on the warning system to the degree in which the operator will only perform an action when an alarm is present and fail to respond when the alarm is not present.

3. Development of a Trust-in-Automation Model

While trust is important to specific automated tasks and outcomes (especially use and performance), the factors that make up these relationships are of critical importance to the development or degradation of trust in automation. However, despite the number of trust definitions available, there is a lack of consensus among experts. Billings and colleagues (2012) reviewed 282 definitions of trust (i.e., 200 interpersonal trust definitions, 32 human-robot trust definitions, and 50 trust-in-automation definitions). These automation trust definitions highlight a number of antecedents that are important to trust development (see figure 2) and support the need for a meta-analytic approach to understanding trust in automation.

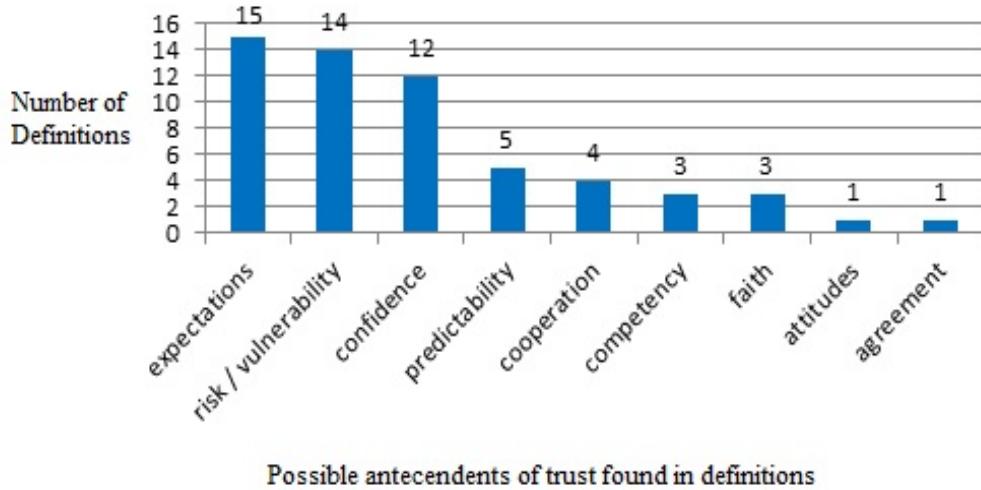


Figure 2. Antecedents of trust from definitions of trust in automation.

Trust definitions within the automation domain range from a broad definition, “a human’s willingness to accept direction from an automated system” (Fan et al., 1998) to the specific, “the extent to which a user is confident in, and willing to act on the basis of recommendations, actions, and decisions of an artificially intelligent agent” (Madsen and Gregor, 2000, p. 1). Refer to appendix A for a list of definitions associated with human-automation interaction, and appendix B for a complete list of trust-in-automation definitions. This diversity within definitions is seen in the other domains of trust as well, supporting the idea that there is no universal definition of trust. However, one of the most referenced definitions of trust in automation is “the attitude that an agent will help achieve an individual’s goals in a situation characterized by uncertainty and vulnerability” (Lee and See, 2004, p. 51).

3.1 Theoretical Model of Human-Automation Trust

To identify potential antecedents of trust development in human-automation interaction, existing literature on trust in automation (both theoretical and empirical) was reviewed. The literature suggests that several factors play important roles in trust development. Some factors involve the human directly, while others focus on aspects of the automation. Other factors deal with various aspects of the operational environment. Therefore, the antecedents of trust are hereby divided by three main factors: the human, the automation, and the environment (see figure 3). The following section will analyze the empirical evidence of human-automation trust through meta-analytic procedures. The findings from this analysis will then be used to update the model of human-robot trust.

Human Operator	Automation	Environment
<p>Human Traits</p> <p>+* Age +Gender +Ethnicity +Personality</p> <p>Human States</p> <p>Fatigue Stress Attentional control</p> <p>Cognitive Factors</p> <p>+* Understanding the automation +* Ability to use automation +* Expectancy of automation</p> <p>Emotive Factors</p> <p>+Attitudes toward automation Confidence in automation +Satisfaction with automation +* Comfort with automation</p>	<p>Features</p> <p>* Degrees of automation +* Appearance * Mode of communication</p> <p>Capability</p> <p>+* Errors in automation +* Automation behavior(s) Quality/Accuracy * Cueing/Feedback/Alarms</p>	<p>Task-Related</p> <p>+* Proximity +Risk</p>

Note: * represents experimental and + represents correlation findings.

Figure 3. Theoretical model of human-automation trust.

3.2 Factors Associated With the Human

As seen within human-technology interaction, the human component is often suggested to be of utmost importance; however, the factors associated with the human are often overlooked in empirical research (as seen by the limited number of cited work) or become a secondary focus behind the functional capabilities of the system. Here we discuss trust as a human-centric construct in that the human is the one trusting the technology. Therefore, the human user or operator must be considered when examining trust. Within the area of trust in automation, the factors associated with the human can be addressed in terms of human traits and states as well as the cognitive and emotive factors.

3.2.1 Operator Traits and States

There is evidence that stable human traits may be related to how an individual responds to automation, but it is likely that their relationships vary as a function of the characteristics of the automated task (Szalma and Taylor, 2011). For example, many demographic characteristics of the user or operator have been suggested to influence the human-automation trust relationship, including age, gender, ethnicity, and personality. For example, age can impact the types of systems that will be trusted (e.g., driver warning systems, Kircher and Thorslund, 2009) and influence the likelihood that the automation will be used (e.g., decision aids for medication

management, Ho et al., 2005). Ho and colleagues also found that older adults were more likely to trust the automation than younger adults. However, upon further exploration, gender differences do not seem to influence trust development (Merritt and Ilgen, 2008; Stedmon et al., 2007). Some work suggests that ethnicity and personality traits are important to trust development (Merritt and Ilgen, 2008). However, they have not been thoroughly explored in the automation trust literature. These antecedents of trust are more commonly referenced in human-interpersonal trust literature and are therefore included in figure 3.

Dynamic human states, such as stress and fatigue, during human-automation interaction are well-researched areas (see Finomore et al., 2009; Neubauer et al., 2012; Reichenbach et al., 2011; Warm et al., 2008). For the purpose of this work, stress is the “force that degrades performance capability” (Hancock and Warm, 1989). Fatigue is a “reduction in the capacity and desire to react . . . characterized by tiredness and an aversion to the continuation of goal-directed work” (Hancock et al., 2012). In addition, several studies also showed that operators with lower attentional control interacted differently with automated systems than those with higher attentional control (Chen and Terrence, 2009; Chen and Barnes, 2012; Thropp, 2006). Attentional control is defined as “one’s ability to focus and shift attention in a flexible manner” (Chen and Barnes, 2012; Derryberry and Reed, 2002). Participants with lower attentional control tended to rely more heavily on automation, even when the reliability of those systems was low. This research indirectly links human states to trust development; however, additional empirical study is needed in these areas.

3.2.2 Cognitive Factors

The operator’s cognitive factors are hereby divided into three areas of research: (1) understanding how the automation works, (2) ability to use the automation, and (3) expectancy of the automation. While these are most often researched in the interpersonal trust domain, Ashleigh and Stanton (2001) suggest that these areas of research are applicable to the technology domain as well. In addition, these divisions are supported by previous work in the field of trust in automation (see Lee and See, 2004; Madhavan and Wiegmann, 2007).

3.2.2.1 Understanding How the Automation Works

Understanding how to operate the automation is based in part on the ease of learning the system and an individual’s previous experiences. Investigations into ease of learning have yielded mixed results. While one study (Wang et al., 2011) indicates that trust is negatively correlated with ease of learning, others have shown that a novice operator’s trust grows along a typical learning curve with training (Muir and Moray 1996), and it is critical to learning (Swadesh and Kasonf, 1995). Past experiences with technology, specifically automated systems, have a direct impact on trust development as well (Merritt and Ilgin, 2008). For example, Rajaonah (2006) suggests that trust is something that builds over time and use with a system. Work by Sullivan and colleagues (2008) supports the idea that trust builds over time and suggests that prior experiences directly influence how an operator will engage the automation. In the computer domain, research has

shown that with sustained exposure to and use of information technologies, computer users develop trust in the accuracy of the data stored within a computer system despite the fact that there is upwards of 10% inaccuracies due to error (Klein et al., 1997; Parasuraman, 1987; Wiener 1985).

3.2.2.2 Ability to Use the Automation

Another area of the operator's cognitive factors that affects the human-automation trust relationship is the operator's perceived ability to use automation. This includes self-efficacy, workload, and expertise as antecedents of trust. Self-efficacy is often defined as an individual's perceived abilities to successfully carry out an identifiable task (Bandura, 1982; 1997). In the field of automation, self-efficacy affects not only whether or not a human will use automation, but also how the human will perceive ease of use and usefulness (Igbaria and Iivari 1995).

One purpose of automation is to reduce workload, and this has been shown to be successful in both mental workload (Wiegmann et al., 2010) and in the implementation of actions (Yang et al., 2009). Increases in mental workload associated with the automated systems have been shown to lead to degradations of trust in automation (e.g., combat identification tasks, Wang et al., 2011). In their work on adaptive aiding of human-robot teaming, de Visser and Parasuraman (2011) found that human-robot teams benefited from imperfect static automation in high-task-load conditions, and adaptive automation helped alleviate the workload of the operator.

Workload has also been directly tied to expertise and experience with automation. For example, in a surgical task using image-guided navigation, inexperienced users reported increased time pressure and mental demands when using the systems (Manzey et al., 2009). Expertise may also be inhibitory, especially in highly reliable systems where a higher experience level may impair an operator's ability to monitor for unanticipated system states (Bailey et al., 2006). As such, increased expertise with a system can enhance trust development (Rajaonah, 2006).

3.2.2.3 Expectancy of the Automation

Prior to interacting with automation, human operators develop *mental models* or expectations of how the automation should behave. Therefore, this subcomponent of cognitive factors includes the following antecedents of trust: perceived commitment, usefulness, expectations, and benefits of automation. Keil et al. (1995) found that the perceived usefulness (e.g., number of anticipated errors) of an automated system is often dictated by a function of the task or the fit of tool. The perceived benefit of the automation can influence whether or not the automation will be trusted (similar to software systems, Lee et al., 2007). If those expectations are high, the human operator may become overreliant on the automation (Mayer et al., 2006), which can lead to mistrust and misuse of the system. The system's reputation may impact operator expectations. For example, in an experiment involving a planning aid, De Vries and Midden (2008) found trust to be slightly higher when the aid was known to have a positive reputation. Findings also suggest that the number of people (i.e., majority or minority) supporting the reputation did not appear to influence trust development.

3.2.3 Emotive Factors

Emotive factors can be divided into four areas of research: attitudes toward automation, confidence in automation, satisfaction, and comfort with automation. Similar to the previously listed cognitive factors, emotive factors are most often researched in the interpersonal trust domain.

3.2.3.1 Attitudes Toward Automation

Attitudes toward the automation can impact overall system awareness states. Bailey and colleagues (2006) found that operators with positive attitudes toward automation may have too much trust in the system and focus less on the overall system state, which can lead to degraded performance. Ardern-Jones and colleagues (2009) found that errors in the system or difficulty accessing needed information within the system can lead to negative attitudes toward automation. Gao et al. (2006) found that operators with negative attitudes toward the automation (such as after a failure) were more likely to disuse the automation. Additionally, moods and emotions impact trust and liking of a system (e.g., happiness, Merritt et al., 2012) as well as reliance on automated systems.

3.2.3.2 Confidence in Automation

Confidence is often used as a synonym for *trust*. For example, in their evaluation of a navigation system (NaviBase) for Ears, Nose, and Throat surgery, Strauss and colleagues (2006) evaluated trust in the system by measuring user confidence. Other researchers suggest that confidence is one of the antecedents leading to trust development. Operators need to be confident in the functionality of the automation to successfully interact and use said automation. Gao et al. (2006) found that an operator will switch to manual control when confidence-based trust in automation decreases. Operators are also more likely to remain in manual control in the future, even when it is clear that the automation is more efficient than human performance. Therefore, we are including confidence as an antecedent of trust.

There is also debate regarding whether self-confidence should be included in a human-automation trust model. Many researchers suggest that there is an interaction between trust and self-confidence as it pertains to automation use (see Chen and Terrence, 2009; De Vries et al., 2003; Lee and Moray, 1994; Neyedli et al., 2009; Wang et al., 2011). However, authors disagree on the interpretation of this interaction. Lee and Moray (1994) suggest that it is the relationship between trust and self-confidence that leads to automation use (i.e., trust exceeds self-confidence) or manual override control (i.e., self-confidence overrides trust). Rani et al. (2000) suggest that operators who have both high trust and high self-confidence tend to prefer a higher level of automation. Since there is a lack of agreement regarding the relationship between trust and self-confidence, self-confidence will only be discussed here and will not be included in the meta-analysis results that follow.

3.2.3.3 Satisfaction With Automation

As is the case in many other arenas, satisfaction influences human perception of automation. This satisfaction is fostered by the quality of information and service that the automation provides (Lee et al., 2007). Generally, as satisfaction increases, so does trust (Domnez et al., 2006). In one example, Wang and colleagues (2011) found trust to be positively correlated with satisfaction in a combat identification task.

3.2.3.4 Comfort With Automation

Whether or not users are comfortable with an automated aid may influence their perception of the aid and, ultimately, whether or not they trust the aid. The level of comfort an individual has with automation may be dependent on familiarity and proximity (Nakada, 1997; van den Broek and Westerink, 2009), similarity of intent (Verberne et al., 2012), or even the degree of control the automated system has over levels of control, tactics, or strategy of the task (Ward, 2000).

The majority of automated systems function within close proximity to their operators. Interaction typically occurs through a computer-based interface. To improve vehicle user interface design for optimum safety, Takayama and Nass (2008) examined the role of computer proximity (in-car versus wireless) on driving behavior. They suggest that in-car automated systems may be more effective for local information (e.g., climate, car maintenance), while distant computers connected by a wireless connection may be better for global information (e.g., navigational instructions). Additionally, systems showed that drivers felt more engaged with the in-car system, potentially leading to safer driving behavior.

3.3 Factors Associated With the Automation

The primary trust development factors associated with the automation itself include features and capability of the automation. Here we discuss the features of the automation in terms of the degrees of automation (e.g., level of automation), appearance, and mode of communication. The capability of the automation is discussed in terms of errors, behavior, quality/accuracy, and communication through cueing and feedback.

3.3.1 Feature-Based Characteristics

Operators tend to have a fundamental bias toward trust in one's own abilities or other human's abilities rather than technology or automated systems (see Dzindolet et al., 2003; Gao et al., 2006; Hughes et al., 2009). However, research by Ma and Kaber (2007) suggest that *initial trust* can be higher for the automated control aid than a human performing the same function. In addition, Madhavan and Wiegmann (2007) found that trust is higher with novice automation (e.g., provides general assistance) than a novice human, while trust is higher with an expert human than expert automation (e.g., provides specific or detailed assistance). The following features-based antecedents of trust can assist in understanding trust development in automation.

3.3.1.1 Degrees of Autonomy

This subcomponent of automation features includes levels of automation (LOA) and mode of automation (e.g., fixed, adjustable, and adaptive automation) as antecedents of trust. The LOA can range from high to low, with a high score indicative of an automated system where the computer or system is totally autonomous and the human has no control, and low score for a system where the human is totally in control and the computer offers no assistance (for a thorough review of the levels of automation, see Parasuraman et al., 2000). While Rani et al. (2000) found no interaction between trust and the preferred LOA, more recent work suggests that LOA has a direct impact on trust development. For example, the combination of multiple types of automation to provide adaptive assistance is more trusted than individual lower LOAs (Cai and Lin, 2012; Cai et al., 2012). In addition, Merritt and colleagues (2012) suggest that when an individual implicitly perceives automation as “good,” the automated system is more trusted than if it is perceived as having “poor” or “ambiguous” automation.

LOA also ties directly into research on the mode of automation (e.g., fixed, adjustable, and adaptive) through the degree to which the human interacts with the automation. Adjustable automation is a direct interaction with automation in which the user or operator has more direct control over the automation. Adaptive automation is an indirect interaction with the automation that takes into account the operator (e.g., emotional state, performance, and workload) and adapts the type and amount of automation accordingly (e.g., emotion-aware consumer products, van den Broek and Westerink, 2009). Human operators typically trust manual adjustable automation more than adaptive automation (e.g., function allocation tasks, Moray et al., 2000) because of the direct human interaction. However, Looije et al. (2010) suggested that when interacting with adaptive automation, humans prefer adaptive automation that can learn, recognize, and respond to personality differences in humans as well as exhibiting specific personality traits itself.

3.3.1.2 Appearance

If an automated aid or machine is perceived to be aesthetically compatible with its function, it is more likely to be used (Goetz et al., 2003). More specifically, Goetz and colleagues suggest that when the appearance of an automated aid matches the user’s expectations, the automated aid is perceived more positively, and the user is more likely to appraise it positively. Further, general likeability has been shown to be influenced by appearance (Li and Yeh, 2010). Nass and Moon (2000) also suggest the importance of anthropomorphic appearance on automated systems. Pak and colleagues (2012) found that increasing the physical anthropomorphic appearance of an automated aid significantly impacted trust development through subjective assessment as well as objective/behavioral assessment.

3.3.1.3 Mode of Communication

Mode of communication refers to the human sensory system that the automation cues (e.g., visual, auditory, and tactile). Sarter (2006) reviewed guidelines focusing on multimodal

information presentation and the research needed in the area, emphasizing the need to design the various parameters carefully to ensure their consistency with the users' personality to maximize trust. For example, specific experimentation on auditory communication demonstrated that operators tend to trust systems with human speech more than synthetic speech and showed enhanced performance into the human speech condition (Stedmon et al., 2007).

3.3.2 Automation Capability

The capability of automation is one of the most researched areas of automation trust literature. While capabilities are typically task specific, three major areas that can be discussed include: errors, behavior, and cueing or feedback.

3.3.2.1 Errors

Errors are unavoidable in human-automation interaction; however, the goal of design is to reduce the number of errors. Errors are traditionally discussed in terms of both misses and false alarms (see Dixon and Wickens, 2006; Dixon et al., 2007); however, trust literature suggests that the reduction of all types of errors increases the reliability of the system and positively impacts trust development (De Vries et al., 2003). As such, the level of trust is mainly based on the user's perception of the competence of the automated aid (Muir and Moray, 1996). Higher reliability has also been shown to lead to higher operator response frequency (i.e., an indirect measure of trust, Spain and Bliss, 2008) and higher reliance on the automation.

In one study with conflicting findings, Uggirala and colleagues (2004) found that the number of errors presented by a system had no effect on trust, but the authors suggested that this was probably because the number of correct and incorrect responses was held constant for each treatment. Therefore, we typically perceive errors as negative influences on trust development in that when automation has too high of an error rate, operators will not trust the automation and disuse it. However, some errors may assist in trust calibration to reduce overreliance and over-trust in the system, which leads to reduced monitoring of the automation and negative performance.

The rate of errors is also important in the human-automation trust relationship. Yamada and Kuchar (2006) found that in drivers, miss rate was related to the degradation of trust in a system, which led to slower response times. Conversely, it is the degree of difficulty of the task and not the type of error that appears to influence trust level. In a target identification task, Madhavan and Wiegmann (2007) found no significant difference between an easy miss group and an easy false alarm group; however, the difficult errors group trusted the automation more than the easy errors group. Similar findings by Master and colleagues (2005) showed significant change in trust between conservative and risky systems but no difference in trust based on error rates. This suggests that individuals are more willing to trust automation despite errors when the task is difficult.

In general, operators and users of automated systems have enhanced trust in the automation when information is accurate and reliable (Spain and Bliss, 2008; Stedmon et al., 2007). Degraded performance has also been shown when inaccurate information was presented (Sarter and Schroeder, 2001). When multiple automation aids are used simultaneously, the potential for conflicting information to be transmitted by different automated alerting systems can increase. In addition, Song and Kuchar (2003) found that this conflicting information can lead to distrust of one or all of the automated systems. Therefore, the accuracy of the communication becomes increasingly important to trust-related responses.

3.3.2.2 Behavior

Similar to human-interpersonal trust, the behavior of automation influences a user's perceived trust in the automated aid. Importantly, trust in automation is established by consistent and reliable behavior on the part of the automation. Over time, this trust reduces the effort expended by the human user, because as trust is gained, the focus shifts away from observing specific behaviors toward assessing the global disposition of the system (McLeod et al., 2005). Therefore, this subcomponent of automation capability includes the following antecedents of trust: predictability, dependability, and specific types of behaviors.

The quality of the automation includes automation expertise, etiquette, and transparency of communication and behavior. Research shows that users trust specialized (expert) automation more than they do general-purpose automated devices or automation they perceive to be novice (Koh and Sundar, 2010; Madhavan and Wiegmann, 2007). Etiquette of automation refers to a collection of behaviors that indicate that the system can be deemed trustworthy or displays behaviors that are satisfying in accordance to the customs of a culture (Parasuraman and Miller, 2004). Current literature suggests that etiquette is related to trust and can lead to a higher probability of intent errors (Dzindolet et al., 2006; Lee and Moray, 1992; Lee and See, 2004; Lees and Lee, 2007; Merritt and Ilgen, 2008; Parasuraman and Miller, 2004). This research suggests that trust-related etiquette can increase the probability that an operator will disregard what they know about the utility of the automation when deciding to use or not use the automation. Simply put, enhancing automation with etiquette features increases trust in automation, despite previous knowledge or reputation.

Predictability and dependability of the automation are some of the most well-researched areas of trust in automation work. Predictability refers to how well the behaviors of the automation match the operator's expectation of that behavior. Dependability refers to the consistency and effectiveness of a behavior. Systems with high reliability engender the trust of their operator across control, cognitive, and perceptual task types (Bagheri and Jamieson, 2004; Bailey et al., 2006; Bliss and Acton, 2003; Cahour and Forzy, 2009; Cummings et al., 2010; Donmez et al., 2006; Ho et al., 2005; Kazi et al., 2007; Moray et al., 2000). Similarly, predictability influences user trust. If experience with a machine provides predictable outcomes, then operators may start to trust the system (Cahour and Forzy, 2009; Muir, 1994). However, when operators experience

unanticipated reactions from the automation (e.g., unpredictable outcomes), there is a rapid drop in trust that often leads to disuse or a disregard for future information provided by the aid (Wiegmann et al., 2010). Dependable systems, specifically the effectiveness of a warning system, are strongly related to the operator's trust (Yamada and Kuchar, 2006). When examining the relationship of pilots and their automated aids, Tenney et al. (1998) found that pilots wanted the automation to be dependable and provide information that was simple and informative. These qualities were ranked more important than accountability (able to explain its actions), subordination (easily countermanded), flexibility (range of modes and levels), adaptability (reprogrammable), error resistance (refuse erroneous inputs), or error tolerance (compensate for erroneous inputs) of automation behaviors.

3.3.2.3 Cueing and Feedback

Many automated systems provide some level of cueing and/or feedback to the operator. The appropriateness of cues and feedback has been shown to have a direct connection to trust development. In a study examining the implications of installing ACC systems in vehicles, it was found that the development of the driver's trust in the automated system may depend on the system's ability to effectively communicate the status of the ACC to drivers to determine when intervention is necessary (Stanton et al., 2007). Bitan and Meyer (2007) suggest that the availability of information is important to trust development. For example, it was suggested that providing drivers with continuous information about the state of the automation may provide a necessary alternative to providing imminent crash warnings when it fails (Seppelt and Lee, 2007). Further, the amount of feedback sought from an automated system by the operators is directly related to the degree of trust they have that it will perform without failure (Muir and Moray, 1996).

Different types of cueing may be used to provide the user with feedback. An experiment that investigated the impact of automation on young and older adults' abilities to detect threat objects found that spatial cueing (e.g., highlighting a specific target) improved performance for both age groups; conversely, text cueing helped young adults but had no impact on older adults' performance (Wiegmann et al., 2006). Sharples and colleagues (2007) identified the impact of different types of communication (i.e., text, radio, face-to-face) on trust development, in which true commands are trusted more than false commands. Alarms can be designed to provide very specific types of feedback to the operator. It is important that the user understand the necessity and benefit of the alarm. The effect of the type of alarm on trust development appears to be task dependent. For example, Gupta and colleagues (2002) found no significant difference in trust by type of alarm in a collision avoidance system, yet Donmez and colleagues (2006) found that drivers trust visual more than auditory alarms for distraction mitigation. The sensitivity of alarms—specifically, the frequency and duration—also affects trust development and use. Gupta and colleagues (2002) found that a reduced number of alarms led to more trust in a collision avoidance system. Wickens and colleagues (2009) support this finding by suggesting that operators perceive excessive alarms to contain false alerts and are thereby unnecessary. This

leads to distrust in the automation and an operator disregard for true alerts. However, Lees and Lee (2007) found an interesting distinction between false alarms and unnecessary alarms. They found that while false alarms decreased trust and compliance levels, unnecessary alarms (instances where the automated device indicates a hazardous situations, but the human may not view them as hazardous) actually increase trust and compliance levels.

3.4 Factors Associated With the Environment

While factors specific to the human and the automation are important in trust development, there are also factors specific to the environment. These environment-based factors often require an interaction between the human and automation within a specific context. Trust is often a task-dependent construct (refer to section 2). The task domain and the environment that it is completed in can impact trust development. Risk and uncertainty are of essential importance in trust development. Here we discuss risk in terms of both the risk of the automation system as well as the risk from the environment. For example, Beckles et al. (2005) looked at the internal risk of data corruption from the automation of a computerized credential management system. They suggest that the system will not be trusted if the information is either compromised or revoked. Lyons et al. (2011) used factor analysis to examine trust in the context of IT suspicion and determined trust and distrust to be orthogonal constructs, and levels of trust are dependent upon cues in the environment. Borst et al. (2010) investigated automation-based pilot alerting systems for the external risk of the physical terrain. They suggest that trust is an important element in these types of automated systems because of the safety risk associated with this type of human-automation interaction.

4. Analytical Method

4.1 Sample of Studies

A review of empirical and nonempirical articles dealing specifically with human-automation trust was conducted using Web of Science and EBSCOhost databases with *automation* and *trust* as the primary search terms. We also used Google and its derivative Google Scholar to perform searches for the primary search terms. After an initial listing of articles was obtained, the references for these papers were reviewed to determine whether any other related studies could be identified. This process resulted in 343 articles and conference proceedings published between 1960 and 2012. Both empirical studies and nonempirical reports were collected initially.

4.2 Criteria for Study Inclusion

All 343 identified studies were inspected to ensure that they fulfilled the following four criteria for inclusion in the meta-analysis:

1. Each study had to report an empirical examination of trust in which trust was a directly measured outcome of an experimental manipulation. Studies in which trust served as the experimental manipulation were excluded.
2. The empirical examination of trust was directed toward automation. Thus, studies investigating interpersonal trust and human-robot trust were excluded. Empirical studies that focused on trust in automated computer-based systems were included in this analysis.
3. Each included study was required to incorporate human participants who either viewed or participated directly in interactions with the automation through physical, virtual, or augmented means.
4. Each study must include sufficient information to determine effect size estimates. Authors of potentially relevant statistics were contacted for additional statistical data needed to calculate effect size.

Of the original 343 articles on human-automation trust that were collected, 287 were immediately omitted because of failure to meet the criteria for inclusion in the meta-analysis. First, 12 articles were written in another language other than English or could not be located. Second, 57 articles investigated trust in something other than automation (e.g., financial trusts, interpersonal trust, robotics). Third, 218 articles did not directly measure trust and were excluded from the analysis. Of these discarded articles, 126 discussed theoretical underpinnings for trust and potential antecedents of trust in automation, 48 introduced factors involved in human-automation interaction, and 44 discussed programming, automation design, and/or development.

A total of 56 empirical articles were identified; however, 27 of these articles had insufficient information to calculate effect size. Authors were contacted via email and were given 5 weeks to respond with additional information. Of these studies, 14 were not included in the final analysis. It is important to note that rejecting primary studies in a meta-analysis is a common occurrence and is necessary to ensure meaningful results when combining effect sizes across studies.

The 42 papers meeting the inclusion criteria are identified in appendix C of this report by either an asterisk (*) or a cross (+) appearing in front of the first author's name. The asterisk (*) represents those studies included in the experimental analyses. The cross (+) represents those studies included in the correlational analyses (see also appendix D).

4.3 Coding of Studies

Available study characteristics from each experiment were coded, including, but not limited, to the following: dependent variable(s), independent variable(s), statistical analysis used, test values, degrees of freedom, means, standard deviations, alpha level, and statistical significance. If more than one variable was manipulated in a study, each independent variable was coded and analyzed separately. Several additional variables were also coded, including the following: (1) type of task, (2) participant population, (3) type of trust (e.g., trustworthiness, general trust), and

(4) main moderator (human, automation, or environment), submoderator (refer to figure 4), and antecedent of trust (described in section 3). Participant population and type of trust were not included for analysis because of the lack of variation between studies.

4.4 Effect Size

The studies included in effect size calculation contained both correlational and group design data, therefore the use of multiple meta-analytic methods (Pearson's r and Hedges' g) was necessary. The correlational effects represent an association between trust and the given factor. Hedges's g indicates the standard difference between two means in standard deviation units. From these we can gather correlational and causal inferences between trust and any given factor. Through both types of meta-analytic effects, the more positive the effect represents a higher level of trust. Findings were interpreted using Hedges' g and Pearson's r established ranges for small ($g \leq .20$, $r \leq .10$), medium ($g = .50$, $r = .25$), and large ($g \geq .80$, $r \geq .40$) effect sizes.

4.5 Variance Estimates

Several variance estimates were calculated. First, variability of the effect sizes themselves (s^2_g) and variability due to sampling error (s^2_e) were estimated. Next, these two values were used to compute the residual variance (s^2_δ). A large (s^2_δ) is an indication that the effect sizes may be heterogeneous, and therefore one or more variables are likely to be moderating the magnitude of that particular effect. A final check for homogeneity of variance (s^2_e/s^2_g) was calculated (proportion of total variance accounted for by sampling error). Hunter and Schmidt (2004) suggest that an outcome here of 0.75 or greater implies that the remaining variance is due to statistical artifacts, and such cases are therefore interpreted as indicating homogeneity of variance among the effect sizes. However, large residual variance and small homogeneity of variance may also be due to a small number of studies, as is evident in some of the following results.

5. Results

The 42 papers meeting the inclusion criteria yielded a total of 166 experimental effect sizes and 63 correlational effect sizes. Following organization of the studies, three main types of analyses were conducted: trusts preference for human or automation assistance (section 5.1), trust in type of task by cognitive, control, and perceptual aids (section 5.2), and moderator analyses (section 5.3 and 5.4). Moderator analyses can be directly linked to figure 3 discussing the human-, automation-, and environmental-related factors of trust.

5.1 Preference for Human or Automation Assistance

There is debate in the literature as to how humans trust technology. While some literature has suggested that human users of technology tend to trust themselves or other humans more than technology, others suggest the exact opposite (see Dzindolet et al., 2001; Lyons and Stokes,

2012). Three empirical studies on how humans trust in automation, yielding nine statistics, were obtained (see De Vries et al., 2003; Ma and Kaber, 2007; Madhavan and Wiegmann, 2007). The Lyons and Stokes (2012) study was not retained, as it measured reliance, not specifically trust. Similarly, the study by Dzindolet and her colleagues (2001) was not retained, as it focused on disuse and misuse of automation, and not directly trust development.

Results ($\bar{g} = -1.30$) support the finding that operators of automation tend to trust themselves or other humans more than the technology (table 3). Although the results suggest large variability in the effect sizes themselves and sampling error, the proportion of total variance accounted for by sampling error (+.75) may be indicative of the small number of studies. There were no correlation-based analyses conducted for this factor. This finding is important to keep in mind when designing automated systems.

Table 3. Meta-analytic results for perception of trust in a human or automation for a task.

Category	k	\bar{g}	s_g^2	s_e^2	s_δ^2	s_e^2/s_g^2	95% CI		N
							Lower	Upper	
Human vs. Automation	3	-1.30	.81	.61	.21	.75	-2.18	-.41	143

k = number of studies.
N = sample size.
 s_g^2 estimates the variability of the effect sizes themselves.
 s_e^2 estimates the variability due to sampling error.
 s_δ^2 is an estimate of the residual variance.
 (s_e^2 / s_g^2) is a calculation of homogeneity of variance.

5.2 Task-related Automation

While 30 experimental studies yielding 164 experimental effect sizes met the original selection criteria, this analysis only included studies that were specifically categorized by the task-related type of automation (i.e., cognitive, perceptual, or control aids). Therefore, 27 experimental studies, which yielded 155 experimental effect sizes, were included for analysis. These results, shown in table 4, indicated there was a moderate global effect concerning trust and automation ($\bar{g} = +0.48$). As the confidence interval here excluded zero, we can assume this is a substantive and consistent effect. The subdivision of this global effect into the three types of task-related automation indicated that the cognitive (13 studies, 72 statistics), perceptual (6 studies, 14 statistics), and control (8 studies, 68 statistics) aids all had a moderate effect on trust development. All findings appear to be consistent; however, the check for the homogeneity of variance for the cognitive aids suggests that the remaining variance may be due to statistical artifacts. This finding allowed us to complete all additional analysis as a complete sample without the need to consider task type as a moderating variable.

Table 4. Meta-analytic results for trust in task-based automation.

Category	k	\bar{g}	s_g^2	s_e^2	s_δ^2	s_e^2/s_g^2	95% CI		N
							Lower	Upper	
Type of Automation	27	.48	.38	.26	.12	.69	.28	.68	999
Cognitive Aids	13	.41	.20	.20	.00	1.00	.14	.67	533
Perceptual Aids	6	.62	.63	.30	.33	.48	.18	1.06	134
Control Aids	8	.51	.54	.36	.18	.67	.09	.93	333

k = number of studies.
 N = sample size.
 s_g^2 estimates the variability of the effect sizes themselves.
 s_e^2 estimates the variability due to sampling error.
 s_δ^2 is an estimate of the residual variance.
 (s_e^2 / s_g^2) is a calculation of homogeneity of variance.

Correlation analyses, including 16 studies and 63 effect sizes, were also conducted. Ten studies (43 effect sizes) were included in cognitive aids, yielding a moderate to large effect ($\bar{r} = +0.39$) on trust development. Perceptual aids yielded a moderate effect ($\bar{r} = +0.37$) on trust development; however, this result was limited to one study. Five studies (19 effect sizes) were included in control aids, yielding a small effect on trust development ($\bar{r} = +0.12$).

5.3 Human-Related Factors

Theoretical work across technological domains suggests the importance of the human element in trust development. Nine studies (54 statistics) were included for analysis, with three being specific to age, four specific to cognitive factors, and three specific to emotive factors. Overall, the human element has a moderate effect ($\bar{g} = +0.49$) on trust (table 5). When looking specifically at the submoderating effects of age, we found a moderate effect ($\bar{g} = +0.44$) on trust development. The results of these three studies suggest that automation is trusted more by older adults than by younger adults. Only one study discussed the correlation between age and trust, so no additional analyses were conducted. The submoderating effect of cognitive factors suggests a small to medium effect ($\bar{g} = +0.39$). Additional research should be conducted in this area to solidify the effects of cognitive traits on trust development. Three experimental studies on emotive factors of trust development yielded a moderate to large effect ($\bar{g} = +0.72$) on trust development. Six studies, yielding 11 effect sizes, were included for correlation-based analysis of emotive factors. This yielded a small to medium effect ($\bar{r} = +0.16$), suggesting that trust and emotive factors are indeed related, albeit small.

Table 5. Meta-analytic results for human-related factors on trust in automation.

Category	k	\bar{g}	s_g^2	s_e^2	s_δ^2	s_e^2/s_g^2	95% CI Lower	95% CI Upper	N
Human	9	.49	.08	.13	-.05	1.70	.25	.72	395
Traits (Age)	3	.44	.15	.09	.06	.63	.09	.79	143
Cognitive Factors	4	.39	.01	.15	-.14	15.39	.01	.77	162
Emotive Factors	3	.72	.01	.18	-.17	21.18	.24	1.20	104

k = number of studies.
N = sample size.
 s_g^2 estimates the variability of the effect sizes themselves.
 s_e^2 estimates the variability due to sampling error.
 s_δ^2 is an estimate of the residual variance.
 (s_e^2 / s_g^2) is a calculation of homogeneity of variance.

5.4 Automation-Related Factors

Automation-related factors were the most researched area of trust in automation with 22 studies (100 statistics). Overall analysis of the automation-related factor suggests a moderate effect ($\bar{g} = +0.53$) on trust development (table 6).

Table 6. Meta-analytic results for automation-related factors on trust in automation.

Category	k	\bar{g}	s_g^2	s_e^2	s_δ^2	s_e^2/s_g^2	95% CI Lower	95% CI Upper	N
Automation	22	.53	.52	.31	.21	.59	.29	.78	766
Features	8	.35	.17	.36	-.19	2.12	-.10	.79	270
Capability	16	.70	.87	.30	.57	.35	.41	.99	517
Behavior	10	.79	.50	.29	.22	.57	.44	1.15	437
Error	3	.44	.36	.09	.28	.24	.11	.77	140
Feedback	6	.45	1.93	.82	1.11	.43	-.28	1.18	140

k = number of studies.
N = sample size.
 s_g^2 estimates the variability of the effect sizes themselves.
 s_e^2 estimates the variability due to sampling error.
 s_δ^2 is an estimate of the residual variance.
 (s_e^2 / s_g^2) is a calculation of homogeneity of variance.

A more detailed look at the submoderating factors of features and capabilities provides a more detailed understanding of the findings. Literature suggests a theoretical importance of automation features on trust development. However, the effects of correlation analysis based on only two studies ($\bar{r} = +0.16$) and experimental analysis ($\bar{g} = +0.35$) include zero in the confidence interval, suggesting an unstable effect. Analyses of automation capabilities showed a moderate correlational effect on trust ($\bar{r} = +0.39$) and moderate to large experimental effect ($\bar{g} = +0.70$) on trust development. The antecedents of the automation capabilities, behavior ($\bar{g} = +.79$) and error ($\bar{g} = +0.44$), were also analyzed. These results suggest that the capability of the automation is important to trust development in that the behaviors should be reliable and that lower error rate leads to more trust in the system.

6. Discussion

Roboticians are more recently attempting to extend the classification of a robot beyond that of traditional automation to include the importance of cognition and intelligence (see Fong et al., 2001; Yagoda, 2011), as well as the environment (see Groom, 2008; Lin et al., 2008). The types of interaction, the number of systems a user may interact with, the environment, and the physical nature of the robots (e.g., complex, dynamic control systems, exhibition of autonomy and cognition) further differentiate HRI from human-computer or human-machine interaction (Scholtz, 2003). However, the area of automation and trust in automation overlaps with human-robot trust to some degree and can help us better understand human-robot trust and extend the human robot trust model first discussed in Hancock et al. (2011, see also figure 1). Figure 4 represents the updated descriptive model of human-robot trust that takes into account the findings from this human-automation trust meta-analysis.

Human	Robot	Environment
Demographic Traits Age Gender Ethnicity/Culture Personality States Fatigue Stress Attentional Control Cognitive Factors Understanding Ability to use/Attention Expectancy Emotive Factors Attitudes Confidence Satisfaction Comfort	Features Levels of Automation Appearance/Anthropomorphism Type Robot Personality Communication Mode Capability Reliability/Errors Behaviors(s) Feedback/Cueing/Alarms	Task-Related Risk/Uncertainty Physical Environment Task Type/Multitasking Team Collaboration In-group Membership Shared Mental Models

Figure 4. Revised human-robot descriptive trust model.

A number of changes were made from the original descriptive trust model. The human-related factor was reorganized from ability-based characteristics and human characteristics subheadings to more specific subheadings (i.e., demographic traits, human states, cognitive factors, and emotive factors). The robot-related factor was reorganized from performance-based and attribute-based subheadings to features and capabilities. Findings from this work provided additional support for the importance of communication on trust development. Communication

was also moved from the environmental-related factor to the robot-related factor and discussed in terms of communication mode (robot feature) and feedback (robot capability). Overall findings demonstrated that the human and automation-related factors had a moderate to large effect on trust development. Findings from this study were also used to identify potential training and design benefits specific to human-robot interaction.

6.1 Training Suggestions

1. *Including some degree of error or failure during training may be important in trust calibration.* While our analysis demonstrated that traditionally a low error rate has a moderate effect on trust development ($\bar{g} = +0.44$), Bahner and colleagues (2008) suggested that exposing users to failures during training can be used to reduce complacency and automation bias. An over-trusting operator is more likely to become complacent and follow the suggestions of the automation without cross-checking the validity against other available and accessible information. Automation bias is the operator's tendency to trust the automation even when contradictory information is present or when information provided by the aid is known to be incorrect.
2. *Scenario training may decrease the operators' unwillingness to use automation.* Automation has been shown to provide benefits to tasks that were traditionally accomplished by humans. Our meta-analytic findings suggest that despite these known benefits, operators or users may tend to trust other humans or themselves more than automation ($\bar{g} = -1.30$). Scenario training may assist users or operators by allowing them to compare the utilities of automated and nonautomated control (Beck et al., 2007), which can reduce these effects.
3. *Training can provide additional understanding of the system.* An increase in automation is predicted for the future, especially in the robotic domain. Sharples et al. (2007) suggest that novel technologies for flight deck air traffic control systems have great potential for increasing safety when the system is understood by the team interacting with it. Therefore, operators and users need additional training with capabilities of the systems. Our analysis demonstrated that automation capabilities ($\bar{g} = +0.70$), behaviors effect ($\bar{g} = +.79$), and communication feedback ($\bar{g} = +.45$) between the operator and automation had a large effect on trust development.

6.2 Design Recommendations

1. *LOAs should be reviewed to determine specifications of the automation for a given task.* Often within human-automation interaction, the LOA dictates the type of communication that occurs. Communication in terms of accuracy, feedback, cueing, mode, and access to information was shown to be essential to trust development. Our findings suggested that the features of the automation including LOA, mode of communication ($\bar{g} = +.35$), as well

as the capability of the automation in terms of communication feedback ($\bar{g} = +.45$), were each shown to have a small to moderate effect on trust development.

The most referenced material on levels of automation is the Parasuraman et al. (2000) article on the 10 levels of automation (figure 5). Robots tend to incorporate multiple types of automation across cognitive, perceptual, and control aids. Therefore, these 10 levels may provide too much detail to successfully incorporate and test in the design. One possible solution is a reduction in levels to include human-in-the-loop (manual or frequent human interaction), human-on-the-loop (human monitors and has ability to intervene), and autonomous (no human intervention).

High	10.	The automation decides everything, acts autonomously, ignoring the human.
	9.	The automation informs the human only if it, the robot, decides to
	8.	The automation informs the human only if asked
	7.	The automation executes automatically, then necessarily informs the human
	6.	The automation allows the human a restricted time to veto before automatic execution
	5.	The automation executes that suggestion if the human approves
	4.	The automation suggests one alternative
	3.	The automation narrows the selection down to a few options
	2.	The automation offers a complete set of decision/action alternatives
Low	1.	The automation offers no assistance: the human must make all decisions and actions

Figure 5. Levels of automation (Parasuraman et al., 2000).

2. *Control displays should be appropriately designed to enhance communication.* Many different sensors are utilized in robot design and use multiple modalities (visual, auditory, tactile) to communicate with human operators or users. Reising and Sanderson (2002) suggested that control displays should be appropriately instrumented and designed according to the principles of ecological interface design, otherwise they might lead to misinterpretation. Our analysis suggested that there is a large effect of communication on trust development; however, more research needs to occur to determine the correct communication modality based on task needs and physical environment. In addition, more research needs to be conducted on the effects of the type of aid (cognitive, perceptual, control) on human-automation trust.
3. *Design can have a direct impact on human safety.* Semmer (2005) suggested that trust can impact how operators interact with automation and that designers should include the social and political aspects of design as well as the individualistic needs. Theoretical work in automation suggests the importance of risk and uncertainty in trust development; however, empirical literature is lacking in this domain. The relationship between robot design and safety becomes an even more important area of research as robotic capabilities continue to advance through increased interdependency of multiple types of automation, as well as the societal need for robots to interact in a wide variety of physical environments.

7. Conclusions

Across the years and especially in the more recent decades, we have seen the general functions of the military become ever more subject to technological innovation. This includes all aspects of the military mission, but it is most especially evident in combat and conflict studies. All trends look toward a “distancing” from immediate interaction in which the agency of such distancing is technology. Not solely a mediating influence, advanced technologies promise to become a determining influence in which all decisions we advanced to are thus promulgated by “automation.” That those systems are currently simply design destinations at remote points in space and time are of little comfort to remaining combatants and to perception of the greater public in general. Meanwhile, we are entering into a phase of hybrid control where action is effected by automation but mediated and monitored by remaining humans-in-the-loop. As this latter situation is an interactive one, we have to look to examine the effectiveness of that interaction and the factors that mediate its effect. Here, trust is a vital dimension. A system untrusted is a system unused or, worse, is a system misused. Yet, over-trust brings its own inherent problems. While our overall focus is on the Soldier-robot relationship, we directly acknowledge that this represents a subset of the overall Soldier-automation relationship.

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Appendix A. Definitions

Attentional Control: One's ability to focus and shift attention in a flexible manner (Chen and Barnes, 2012; Derryberry and Reed, 2002).

Automation: (1) Machine execution of functions (Parasuraman et al., 2000); (2) “the execution by a machine agent (usually a computer) of a function that was previously carried out by a human” (Parasuraman and Riley, 1997, p. 231); (3) “the technology that actively selects data, transforms information, makes decisions, or controls processes” (Lee and See, 2004, p. 50).

Cognitive Aids: Provide recommendations to users about the current and potential future states of systems.

Control Aids: Replace varying levels of human (operator/user) action.

Perceptual Aids: Used to assist the operator or user by providing warnings or to assist with pattern recognition.

Autonomy: (1) A capability (or set of capabilities) that enables a particular action of a system to be automatic or, within programmed boundaries, “self-governing” (Defense Science Board, 2012); (2) degree of authority to act on the “World” (Riley, 1989).

Etiquette (system): A collection of behaviors that indicate that the system can be deemed trustworthy, or displays behaviors that are satisfying in accordance to the customs of a culture (Parasuraman and Miller, 2004).

Fatigue: A reduction in the capacity and desire to react (Hancock et al., 2012).

Robot: (1) “Programmable automation to augment human manipulation” (Mahoney, 1997, p. 3); (2) an autonomous system that acts on its own decisions with input from a human operator but may not be completely controlled by a human (Feil-Seifer and Matarić, 2005); (3) the interaction of intelligence and autonomy of the technology (Yagoda, 2011); (4) a complex, dynamic system that shows a degree of autonomy and cognition as it operates in a real-world environment (Fong et al., 2001); (5) perceives the environment through sensor inputs that may or may not require direct human response and has the ability to move in order to manipulate an uncertain physical world by transmitting information at humans or directly acting on the environment (Groom, 2008; Lin et al., 2008).

Self-efficacy: An individual's perceived abilities to successfully carry out an identifiable task (Bandura, 1982; 1997).

Stress: The force that degrades performance capability (Hancock and Warm, 1989).

Appendix B. Comprehensive Automation Trust Definition Set

Definition Citation	Definition
Adams and Webb (2003)❖	Trust is a psychological state involving positive confident expectations and willingness to act on the basis of these expectations. Issues of trust arise in contexts that involve risk, vulnerability, uncertainty and interdependence. Trust expectations are created primarily by the interaction of the perceived qualities of the trustee and contextual factors in play when trust decisions are made (p. 38).
Barber, B. (1983)	<p>Barber defines trust in terms of a taxonomy of three specific expectations that can be extended to the human/machine relationship, according to Muir (1994):</p> <ul style="list-style-type: none"> • our general expectation of the <i>persistence</i> of the natural physical order, the natural biological order, and the moral social order, • our specific expectation of <i>technically competent role performance</i> from those involved with us in social relationships and systems, • our specific expectation that partners in an interaction will carry out their <i>fiduciary obligations and responsibilities</i>, that is, their duty in certain situations to place others' interests before their own.
Bentley et al. (1995)	Trust and familiarity is a process that is partially a function of technology (i.e., trust and familiarity can be embedded in use) (p. 151).
Biros et al. (2004)	<p>“System automation trust is defined as having confidence in and entrusting the system automation to do the appropriate action” (p. 177).</p> <p>In this model, dependability and predictability contribute to an individual’s overall trust in a system’s automation.</p>
Boon and Holmes (1991)	“A state involving confident predictions about another’s motives with respect to oneself in situations entailing risk.”
Cohen et al. (1998)	The perceived probability of the system’s reliability, given certain situations (APT model). “The problem of decision aid acceptance is neither under trust nor over trust, but <i>inappropriate</i> trust: a failure to understand or properly evaluate the conditions affecting good and bad aid performance” (p. 1).
Costa, Roe, and Taillieu (2001)❖	“Trust is a psychological state that manifests itself in the behaviours towards others, is based on the expectations made upon behaviours of these others, and on the perceived motives and intentions in situations entailing risk for the relationship with those others” (p. 228).
Curral (1990)❖	“Relying on someone under conditions of dependence and risk.”
Curral and Inkpen (2002)❖	Trust is the decision to rely on a partner with the expectation that the partner will act according to a common agreement.
Deutsch (1973)❖	“The confidence that one will find what is desired from another, rather than what is feared” (p. 148).

Note: References marked with a ❖ represent definitions that are originally from another domain of trust but are referenced or applied to automation.

Definition Citation	Definition
De Vries et al. (2003)	“We consider trust to be the expectation of a user about the system, that the system will perform a certain task for him or her, while the outcome of that task is uncertain, in that it can have both positive and negative consequences. In other words, an element of risk should be present” (p. 722).
Fan et al. (1998)	A human’s willingness to accept direction from an automated system.
Jeannot et al. (2003)	“Trust is a result of many factors such as reliability of the system and transparency of the functions. Neither mistrust nor complacency are desirable” (p. 4).
Lee and See (2004)	“Trust can be defined as the attitude that an agent will help achieve an individual’s goals in a situation characterized by uncertainty and vulnerability” (p. 51).
Luhmann (1979)❖	Mechanism to reduce feelings of uncertainty via a continuous feedback loop the person monitors the behavior of the trustee to determine whether the trust vested in the person is justified.
Madhavan and Wiegmann (2007)	“Trust refers to the expectation of, or confidence in, another and is based on the probability that one party attaches to co-operative or favourable behaviour by other parties (Barber 1983, Muir 1987, Hwang and Buergers 1997)” (p. 280).
Madsen and Gregor (2000)	Comprised of the reliability of the system, perceived technical competence of the system, perceived understandability of the system, faith into the system and personal attachment to the system.
Madsen and Gregor (2000)	Human-computer trust is defined in this study to be, the extent to which a user is confident in, and willing to act on the basis of the recommendations, actions, and decisions of an artificially intelligent agent.
Master et al. (2000)	Trust model incorporates four dimensions: competence, predictability, reliability, and faith in a system or machine.
Mayer et al. (1995)❖	“[W]illingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that party” (p. 712).

Note: References marked with a ❖ represent definitions that are originally from another domain of trust but are referenced or applied to automation.

Definition Citation	Definition
Merriam-Webster Online (2013)	<p>1) a: assured reliance on the character, ability, strength, or truth of someone or something b: one in which confidence is placed</p> <p>2) a: dependence on something future or contingent : hope b: reliance on future payment for property (as merchandise) delivered : credit <bought furniture on trust></p> <p>3) a: a property interest held by one person for the benefit of another b: a combination of firms or corporations formed by a legal agreement, especially : one that reduces or threatens to reduce competition</p> <p>4) archaic: trustworthiness</p> <p>5) a: (1) a charge or duty imposed in faith or confidence or as a condition of some relationship (2) something committed or entrusted to one to be used or cared for in the interest of another b: responsible charge or office c: care, custody <the child committed to her trust></p> <p>— in trust: in the care or possession of a trustee</p>
Merrit and Ilgen (2008)	<p>“Dispositional trust reflects trust in other persons (or machines) upon initially encountering them, even if no interaction has yet taken place” (p. 195).</p>
Merrit and Ilgen (2008)	<p>“... history-based trust is founded on interactions between the person and another person or machine” (p. 195).</p>
Merrit and Ilgen (2008)	<p>“... the stable, trait-like tendency to trust or not trust others, which we call propensity to trust” (p. 195).</p>
Moorman et al. (1993)	<p>“Trust is defined as a willingness to rely on an exchange partner in whom one has confidence (Moorman, Zaltman, and Deshpande, 1992)” (p. 82).</p>
Moray and Inagaki (1999)	<p>“... an attitude which includes the belief that the collaborator will perform as expected, and can, within the limits of its designers’ intentions, be relied on to achieve the design goals” (p. 204).</p>
Muir (1989)	<p>The dynamic nature of trust consist of three dimensions: predictability, dependability, and faith</p>
Muir (1994)	<p>“...an intervening variable that mediates between the automated system and the user’s choice of a control strategy in his/her interaction with the system”</p>
Parasuraman and Miller (2004)	<p>“In practice, user trust should be calibrated to the system and context of its use, users should have accurate beliefs about the reliability of automation (and about their own capabilities)” (p. 52).</p>
Rajaonah et al. (2006)	<p>“We define trust as a psychological state resulting from knowledge, beliefs, and assessments (Castelfranche & Falcone, 2000) related to the decision making situation, that creates confident expectations (Corritore, Kracher, and Wiedenbeck, 2003) for human machine system performance and guides operator reliance on automation (Lee & See, 2004)” (p. 102).</p>
Rempel et al. (1985)❖	<p>“... A generalized expectation related to the subjective probability an individual assigns to the occurrence of some set of future events” (p. 96).</p>

Note: References marked with a ❖ represent definitions that are originally from another domain of trust but are referenced or applied to automation.

Definition Citation	Definition
Rempel and Holmes (1986)❖	“In a general sense, trust is the degree of confidence you feel when you think about a relationship” (p. 28).
Ross (2008)	“To measure objective trust of an automated system, reliance was analyzed. Reliance was measured as the combined total of the times the participant agreed with the aid” (p. 38).
Rotter (1967)❖	“A generalized expectancy held by an individual that the word, promise, oral or written statement of another individual or group can be relied upon” (p. 653).
Scanzoni (1979)❖	An actor’s willingness to arrange and repose his or her activities on [an] Other because of confidence that [the] Other will provide expected gratifications.
Singh et al. (1991)	Complacency is a set of attitudes involving uncritical trust towards, over reliance on, excessive confidence in, and other related attitudes towards automation technology.
Swadesh and Kasouf (1995)	“Trust is related to a number of characteristics of the researcher: sincerity, integrity, tactfulness, timeliness and ability to keep information confidential” (p. 199).

Note: References marked with a ❖ represent definitions that are originally from another domain of trust but are referenced or applied to automation.

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Appendix C. References of Experimental and Correlational Articles

* Abe, G.; Richardson, J. The Effect of Alarm Timing on Driver Behavior: An Investigation of Differences in Driver Trust and Response to Alarms According to Alarm Timing. *Transportation Research Part F: Traffic Psychology and Behaviour* **2004**, 7 (4/5), 307–322. doi:10.1016/j.trf.2004.09.008

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*de Vries, P.; Midden, C. Effect of Indirect Information on System Trust and Control Allocation. *Behavior & Information Technology* **2008**, 27 (1), 17–29. doi:10.1080/01449290600874956

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Appendix D. Organization Results

Preference for Human or Automation Assistance (Section 5.1)

De Vries et al. (2003)

Ma and Kaber (2007)

Madhavan and Wiegmann (2007)

Task-Related Automation (Section 5.2)

	Empirical	Correlation
Cognitive Aids	Bagheri (2004) Bagheri and Jamieson (2004) Cai and Lin (2012) Cai et al. (2012) De Vries and Midden (2008) De Vries et al. (2003) Ho et al. (2005) Koh and Sundar (2010) Madhavan and Wiegmann (2007) Madhavan et al. (2006) Merritt et al. (2012) Neyedli et al. (2009) Pak et al. (2012)	Bagheri and Jamieson (2004) Bagheri (2004) Cummings et al. (2010) Dzindolet et al. (2003) Lee and Chung (2009) Lee et al. (2007) Merritt and Ilgen (2008) Neyedli et al. (2009) Wang et al. (2009) Wang et al. (2011)
Perceptual Aids	Abe and Richardson (2004) Abe and Richardson (2005) Bliss and Acton (2003) Gupta et al. (2002) Koustanai et al. (2012) Lorenz et al. (2002)	Abe and Richardson (2006)
Control Aids	Donmez et al. (2006) Manzey et al. (2009) Moray et al. (2000) Rajaonah (2006) Smyth (2007) Spain and Bliss (2008) Stedmon et al. (2007) Verberne et al. (2012)	Donmez et al. (2006) Muir and Moray, 1996 Rajaonah (2006) Rajaonah et al. (2008) Spain and Bliss (2008)

Human-Related Factors (Section 5.3)

	Empirical	Correlation
Age	Donmez et al. (2006) Ho et al. (2005) Pak et al. (2012)	Merritt and Ilgen (2008)
Cognitive Factors	De Vries and Midden (2008) Koustanai et al. (2012) Manzey et al. (2009) Rajaonah (2006)	Dzindolet et al. (2003) Lee et al. (2007) Merritt and Ilgen (2008) Rajaonah et al. (2008) Spain and Bliss (2008) Wang et al. (2011)
Emotive Factors	Koustanai et al. (2012) Neyedli et al. (2009) Verberne et al. (2012)	Donmez et al. (2006) Lee and Chung (2009) Lee et al. (2007) Merritt and Ilgen (2008) Wang et al. (2009) Wang et al. (2011)

Automation-Related Factors (Section 5.4)

	Empirical	Correlation
Features	Cai and Lin (2012)	Dzindolet et al. (2003)
	Cai et al. (2012)	Lee and Chung (2009)
	Lorenz et al. (2002)	
	Merritt et al. (2012)	
	Moray et al. (2000)	
	Pak et al. (2012)	
	Stedmon et al. (2007)	
	Verberne et al. (2012)	
Capabilities	Abe and Richardson (2004)	Abe and Richardson (2006)
	Abe and Richardson (2005)	Bagheri and Jamieson (2004)
	Bagheri (2004)	Bagheri (2004)
	Bagheri and Jamieson (2004)	Dzindolet et al. (2003)
	Bliss and Acton (2003)	Lee and Chung (2009)
	De Vries et al. (2003)	Lee et al. (2007)
	Donmez et al. (2006)	Muir and Moray (1996)
	Gupta et al. (2002)	Rajaonah (2006)
	Ho et al. (2006)	
	Koh and Sundar (2010)	
	Madhavan and Wiegmann (2007)	
	Madhavan et al. (2006)	
	Moray et al. (2000)	
	Smyth (2007)	
	Spain and Bliss (2008)	
	Stedmon et al. (2007)	

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